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Path Planning of Multiple Unmanned Marine Vehicles for Adaptive Ocean Sampling Using Elite Group-Based Evolutionary Algorithms

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Abstract

This paper presents elite group-based evolutionary algorithms (EGEA) for adaptive ocean sampling using multiple unmanned marine vehicles (UMVs). The EGEA integrate a group-based framework and elitist selection methods into evolutionary path planner, which combine main advantages of these two techniques.The group-based framework allows each offspring individual of evolutionary algorithm to generate its own group of new solutions with a certain probability. Two elitist selection methods, herein referred to as group individual elitist selection (GIES) and whole population elitist selection (WPES), are proposed to facilitate selecting preferable solutions to be passed on to the next generation in the procedure of evolutionary algorithms. The EGEA path planners based on simulated annealing algorithm (SA) and particle swarm optimization (PSO) are tested to find trajectories for multiple UMVs to collect maximum interested ocean information from regions under investigation. The mixed integer linear programming (MILP) is also described and evaluated with the proposed EGEA for solving the adaptive sampling problem. Simulation results show that the whole elite group-based simulated annealing algorithm (WEGSA) is able to generate trajectories with more information gain from regions of high scientific interest with constrained energy of multiple UMVs than other techniques. Monte Carlo simulations demonstrate the inherent robustness and superiority of the proposed planner based on the EGEA in comparison with other techniques.

Keywords Path planning · Multiple unmanned marine vehicles · Adaptive ocean sampling · Simulated annealing algorithm · Particle swarm optimization

1 Introduction

The capability to observe, track and estimate the ocean phenomenon is crucial for oceanic applications, such as ocean forecasting, pollution management, marine resources utilization and ecosystem monitoring [1, 2]. However, the practical inability to make extensive and sustained measurements and the limited information at depth to complement the satellite measurements make it a challenging task for ocean monitoring [3]. To successfully sense and sample the ocean, great efforts have been made by scientists in investigating ocean observation systems, which have been developed rapidly in the last two decades and open the door of acquiring more accurate spatiotemporal measurement resolution [4]. Unmanned marine vehicles (UMVs), such as autonomous surface vehicles (ASVs) and autonomous underwater vehicles (AUVs), are important and valuable tools for exploring the ocean, travel through the ocean freely and fast, and can be equipped with sensors to take measurements and collect data in adaptive sampling missions [5].

Path planner is a core part of UMV's guidance module, which allows UMV to autonomously compute optimized path for adaptive ocean sampling. Theoretical and field researches have been conducted on planning the paths of UMVs [6, 7]. Yang et al. [8] used artificial potential field (APF) algorithm for motion planning and obstacle avoidance of multi-HUG formation. Multi-dimensional rapidly exploring random trees star (RRT*) algorithm was

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introduced by Cui et al. [9], which returns feasible, and obstacle-free paths that steer vehicles from the initial state to the goal state for the multi-AUVs system. Song et al. [10] proposed a novel multi-layered fast marching (MFM) method to generate practical trajectories for ASVs when operating in a dynamic environment. The purpose of these earlier researches focused on planning and determining feasible strategies that minimize a chosen energy or time-related cost criterion. However, considerable work has to be done to develop advanced techniques for path planning of multi-UMVs that explicitly address the problem of adaptive ocean sampling.

A small but significant literatures on path planning of UMVs have been available that specifically focus on the adaptive ocean sampling problem that acquires meaningful information from data collection in regions under investigation. Yilmaz et al. [3] presented the first attempt at formulating a multi-AUVs path planner for adaptive ocean sampling using MILP. Jaillet et al. [11] proposed the Transition-based RRT (T-RRT) algorithm that combines the exploration strength of the RRT and the efficiency of stochastic optimization method, for path planning of one robot in high-dimensional cost spaces. Then, a new algorithm named Zig-Zag in the Tranquil Ocean Path Planner (ZZTOPP) was proposed by Smith et al. [12] to plan the path of glider. A branch and bound method inspired by feature selection algorithm was applied to find path of a AUV that maximizes the reduction in variance of the ocean field being estimated [13]. Sampling-based motion planning algorithms were proposed by Geoffrey et al. [14] for generating informative trajectories of robots to achieve efficient information gathering in continuous space with motion constraints. The above mentioned algorithms are used for solving off-line adaptive sampling problem, which can generate globally optimized paths. Meanwhile, some researchers have developed on-line path re-planning algorithms considering spatiotemporal variations of environment phenomena for adaptive sampling problem [15–17]. Those algorithms are effective when applied to small scale adaptive ocean sampling problem, but may not necessarily be valid when dealing with the complex large scale adaptive ocean sampling problem considering energy constraints of multi-UMVs. When it comes to large scale ocean environmental sampling, ocean phenomenon may last for days or weeks over scales of tens or hundreds of kilometers with high spatial complexity, therefore, an effective global path planning algorithm is of vital importance to solve the complex adaptive ocean sampling problem. In this research, we focus on developing global off-line path planning algorithms of multi-UMVs for large scale adaptive ocean sampling mission with a-priori known nowcast environment map, and on-line path re-planning algorithms will be developed in our future works.

Evolutionary algorithms, on the other hand, have been successfully utilized to solve large scale path planning problem. Genetic algorithm (GA) was proposed to find rendezvous trajectories for multiple gliders with minimal energy consumption [18]. Particle swarm optimization (PSO) was applied to plan trajectories of AUVs that maximum ocean measurements collection in regions under investigation [19]. Simulated annealing algorithm (SA) was applied to plan optimal route for robot operating in dynamic environments with both static and dynamic obstacles [20]. Zeng et al. [21] came up with the shell space decomposition (SSD) scheme to be integrated with a quantum-behaved particle swarm optimization (QPSO) based path planner to find an optimal and efficient path for an AUV navigating through a variable ocean environment in the presence of obstacles. Meanwhile, Zeng et al. [22] proposed B-Spline based QPSO for path planning, which outperforms RRT/RRT*, GA and PSO methods, as well as the deterministic A* method for solving the optimal path planning problem of an AUV operating in environments with ocean currents with minimization of time usage. Zhuang et al. [23] integrated particle swarm optimization (PSO) algorithm with Legendre pseudospectral method (LPM) for finding time-optimal collision-free path of an AUV. Therefore, evolutionary algorithms can be a choice to be applied for solving the multi-UMVs path planning problem associating with adaptive ocean sampling.

However, there are still a number of challenges for evolutionary algorithms when solving this problem. Earlier works on this topic have been dominated by single-UMV planning. In real applications, it is beneficial to use multiple-UMVs to perform large scale sampling missions and survey tasks, since multiple-UMVs can reduce mission time, permit a wider area of data acquisition and improve outcomes of one mission [24]. The number of UMVs involved in ocean sampling mission relates to the dimension of the solution space and computational complexity grows exponentially for high dimensional search space [25]. In addition, the problem of constrained energy resources available for UMVs to conduct science missions over long periods arises [26]. It is required that the path planner is able to incorporate battery capability of every vehicle to ensure that the mission can be accomplished both safely and optimally [27].

Considering the above challenges, to increase searching efficiency of evolutionary path planner and save computation time, elite group-based evolutionary algorithms (EGEA) is proposed in this research. The EGEA integrate a group-based framework and elitist selection methods into evolutionary path planner, which combine the main advantages of these two techniques. These include the group-based framework allowing each offspring individual of evolutionary algorithm to generate its own group of new solutions with a certain probability; and two elitist selection methods, herein referred to as group individual elitist selection (GIES) and whole population elitist selection (WPES), are proposed to facilitate selecting preferable solutions to be passed on to the next generation in the procedure of evolutionary algorithms. The EGEA path planners based on simulated annealing algorithm (SA) and particle swarm optimization (PSO) are tested offline to find optimized trajectories for multiple UMVs to collect maximum interested ocean information based on an available cost map under investigation. Meanwhile, mixed integer linear programming (MILP) [3] is also described and compared with the EGEA for the adaptive sampling problem.

This paper is organized as follows. Section 2 deals with mathematical models including objective function and motion constraints of single UMV cases and multi-UMVs cases in a 2D ocean environment. Section 3 elaborates preliminary optimization algorithms and discusses the proposed approach as well as its integration into evolutionary path planner. Section 4 presents four case studies under various scenarios and robustness assessment using Monte Carlo trials. Finally, Section 5 gives the conclusion and ideas for the future works.

2 Problem Formulation

In this research, the multi-UMVs path planning problem associating with adaptive ocean sampling is formulated to generate offline trajectories for UMVs so that they can collect as much data as possible in high scientific interest areas with constrained energy in an available cost map. Our primary concern is increasing the searching efficiency of evolutionary path planner for UMVs with simplified dynamics in large-scale ocean sampling. As for planning strategies of AUVs in 3D ocean environments, readers can refer to existing works [28–30] for more details. The following assumptions are considered in formulating multi-UMVs path planning problem:

Assumption 1 This research primarily focuses on a high-level planning architecture in scale of tens of kilometers and UMVs are equipped with GPS, therefore it is assumed that UMVs are programmed to resurface every hour for localization and control strategies can drive the vehicles to track the planned trajectories with simplified dynamics [31, 32].

Assumption 2 The water-referenced speed of each UMV is assumed to be a constant. Since this speed is proportional to the cube root of thrust [33], the vehicle has constant thrust power and thus the energy consumed along the path is a constant multiple of the distance traveled, and consequently, energy constraints of UMVs can be assumed as maximum distance they can travel.

Assumption 3 When an UMV passes a grid in a 2D discrete ocean environment field, the vehicle obtains not only the sampling value of this grid, but also sampling values of the adjacent eight grids. And, when the UMV moves to next grid, sampling values of these nine grids will turn to zero to avoid repeated calculation.

Workspace $\mathbb{W} = \mathbb{R}^2$ is modeled as a patch of ocean environment field. A set of $\mathbb{S}$-UMVs are deployed to travel with constant velocity V from their initial position $P_0 = [x_0, y_0]$ to take measurements. In this research, the potential UMVs path is represented by a sequence of points along the path $P_s = \{P_1, P_2, ..., P_{H_s}\}$, where H_s is the total number of passed grids belonging to the s_{th} vehicle.

Additionally, UMVs need to be retrieved before energy is depleted. According to Assumption 2, the energy consumption of UMV is related to the range of UMV, hence the path length of each UMV in simulation cannot exceed a specified constant L_{max}.

Therefore, the multi-UMVs path planning problem associating with adaptive ocean sampling is formulated as the following maximization problem:

$$\begin{aligned} & P_s^* = \underset{P_s \in P}{argmax}\, F(\mathbb{S}, V, \mathbb{W}, P_0) \\ s.t. \quad & \dot{V} = 0, \\ & L_s < L_{max}, s = 1, 2, ..., \mathbb{S} \end{aligned} \tag{1}$$

where F is the data collection objective function in this research and will be discussed in the next subsection.

2.1 Optimization Criterion

The purpose of this research is to find mathematically optimized paths that maximize data collection in the regions of high scientific interest with constrained energy of UMVs.

For single UMV case, objective function is defined to maximize the total collected sampling value along the path of the vehicle over a 2D predefined research region. Therefore the objective function of the ocean sampling problem of single UMV case can be written as:

$$F_{single} = \sum_{\lambda=1}^{H_1} f_\lambda \tag{2}$$

where F_{single} is the sampling value collected by an UMV for one mission, f_λ denotes the obtained sampling value of λ_{th} passed grid in the 2D discrete ocean environment map.

For multi-UMVs case, it is necessary to take consideration of collision between vehicles. It is dangerous for any vehicle to navigate too close to another one at the same time. Constraints can be constructed as:

$$|P_{r\lambda} - P_{s\lambda}| \geq d_{min} \tag{3}$$

where $d_{r\lambda}$ and $d_{s\lambda}$ is the position of r_{th} and s_{th} vehicle at the same time, and d_{min} is the minimum safety distance in case of collision. Therefore the objective function of multi-UMVs case can be written as:

$$F_{multiple} = max \sum_{s=1}^{\mathbb{S}} \sum_{\lambda=1}^{H_s} f_{s\lambda} \tag{4}$$

where $F_{multiple}$ is the total sampling value of $\mathbb{S}$-UMVs in the fleet, $f_{s\lambda}$ denotes the obtained sampling value of λ_{th} passed grid of s_{th} vehicle.

2.2 Ocean Field Environment

Oceanographic processes show great variability in space and time, last from days to weeks, and cover large areas of hundreds to thousands of square kilometers. In practice, the path planning problem for ocean sampling is generally solved for long-term missions with durations of several days and path length of tens to hundreds kilometers. Marine vehicles, such as Saildrones, equip with thermal imaging camera ("https://www.infinitioptics.com/technology/thermal-imaging") can provide sampling at high spatial (1-5 km) and temporal (1 min) resolution [34]. Meanwhile, National Weather Service (NWS) ("https://www.weather.gov/") can provide ocean data, such as currents, sea temperature, salinity, etc, in 1kmx1km resolution, which have been widely recognized by researchers to be used for ocean research. In this research, we assume that higher temperature zones are where marine scientists need the UMVs to take measurements. Then, temperature data obtained from National Weather Service (NWS) over a predefined area is transformed to a cost map for path planning of multi-UMVs.

Since the following proposed elite group-based evolutionary path planner can handle not only low resolution ocean model but also high resolution ocean model with large space dimensions, the ocean sampling field in this research will focus on a 80km×60km map with temperature value varying from 3.6 to 5.2, which is represented by a 2D discrete grid map with 80×60 grids. On this particular issue, temperature value in each grid is set to be the sampling value.

3 Elite Group-based Evolutionary Path Planner

This section develops preliminary evolutionary algorithms and the proposed group-based evolutionary algorithm with two selection methods for UMVs path planning in the regions of high scientific interest.

For comparison, optimized paths are also computed using mixed integer linear programming (MILP), which is the first proposed algorithm to be implemented to the adaptive ocean sampling problem. For a detailed discussion of MILP, we refer the readers to the complete publication [3].

3.1 Preliminary Evolutionary Algorithms

In this subsection, conventional methods of SA and PSO are elaborated in detail.

3.1.1 Simulated Annealing Algorithm

Simulated annealing algorithm is a well-known form of evolutionary algorithm using a random variation of current solutions [35]. The crucial idea of SA is to use random search, which not only accepts changes that improve the objective function, but also keeps some changes that are not ideal with a probability.

Suppose x_i^n denote the solutions of ith individual in nth iteration. In one iteration, new solutions are generated through movement based on current solutions. The movement can be written as:

$$x_i^{n+1} = x_i^n + random(-1, 1)\eta^{n+1} \tag{5}$$

$$\eta^{n+1} = \eta^n \eta_{damp} \tag{6}$$

where η denotes the movement range of every individual, η_{damp} is damping ratio of η in each iteration. Solutions with better objective function value will be automatically accepted. Meanwhile, to avoid falling into local optimum, worse solutions can also be accepted in a certain probability defined as:

$$p = e^{-\frac{\triangle f}{T_n}} \tag{7}$$

where $\triangle f$ is the change of objective function value between two solutions of one individual and T_n is the temperature for controlling the annealing process. A random number r is used as a threshold to decide whether or not to accept a worse solution. Thus, if $p > r$, the worse solution is accepted; otherwise, the previous solution will be remained. The temperature is updated according to the following equation:

$$T_{n+1} = \alpha T_n \tag{8}$$

where α is a constant close to one. The initial temperature T_0 must be large enough to increase diversity of solutions. As the temperature is decreasing by iteration, the probability of accepting a worse solution decays. Therefore, the final solution is near optimal when the temperature approaches zero.

3.1.2 Particle Swarm Optimization

Particle swarm optimization is generally recognized to be effective for solving path planning problem. The aim of PSO is to find the global best among all the current best solutions until the objective no longer improves or after a certain number of iterations [36].

Let x_i and v_i be the position and velocity of particle i, respectively. The particles are manipulated according to the following equation:

$$\begin{aligned} v_i^{n+1} = &\ w^n v_i^n + c_1 rand_1(p_{best} - x_i^n) \\ &+ c_2 rand_2(g_{best} - x_i^n) \end{aligned} \tag{9}$$

$$x_i^{n+1} = x_i^n + v_i^{n+1} \tag{10}$$

where w_n is the weight factor, c_1 and c_2 are two positive constant parameters, $rand_1$ and $rand_2$ are two random functions in the range [0,1], p_{best} is the best position of the ith particle, and g_{best} is the best position among all particles in the swarm.

In this research, the following functional form for the weight factor is selected as:

$$w^{n+1} = w^n w_{damp} \tag{11}$$

where w_{damp} is damping ratio of w in each iteration.

3.2 Elite Group-based Evolutionary Algorithms

Algorithm 1 IEGEA for adaptive ocean sampling.

Initialization: set initial values of all the parameters, input current environmental information and randomly generate a feasible path for each individual.

```
for n=1 to IT do
    for i=1 to N do
        for j=1 to h do
            Generate new solutions based on
            conventional PSO or SA;
            Evaluate new solution X_j;
        end for
        Select the best solutions X_i^n for ith individual in
        nth iteration;
        Store the best solutions;
    end for
    Update parameters;
end for
```

The main concept of the group-based evolutionary algorithm is to give each individual h chances to create its own group of new solutions in every iteration. Then, two elite selection methods, group individual elitist selection (GIES) and whole population elitist selection (WPES), are proposed to select preferable individuals to be passed on to next generation in each iteration. The group-based evolutionary algorithm with two elitist selection methods are herein referred to as the individual elite group-based evolutionary algorithm (IEGEA) and whole elite group-based evolutionary algorithm (WEGEA).

Algorithm 2 WEGEA for adaptive ocean sampling.

Initialization: set initial values of all the parameters, input current environmental information and randomly generate a feasible path for each individual.

```
for n=1 to IT do
    for i=1 to N do
        for j=1 to h do
            Generate new solutions based on
            conventional PSO or SA;
            Evaluate new solution X_j;
        end for
    end for
    Sort all solutions in nth iteration;
    Store the top N solutions;
    Update parameters;
end for
```

As for IEGEA, the individual with best new solution of each group is chosen to be passed on to next generation. While, WEGEA is to put all the obtained new solutions together, sort them and select the population number of excellent individuals to be passed on to next generation. In other words, IEGEA is to select the individual with best solution of each group in every iteration, while WEGEA is to select the top population number of all the orderly new solutions in every iteration. There is one more point to be noted that the population size must be reduced h times to keep the improved two versions at the same magnitude as the conventional algorithm when comparing the performance between algorithms. Figures 1 and 2 illustrate the core procedure of IEGEA and WEGEA. The pseudo code of IEGEA and WEGEA are given in Algorithm 1 and Algorithm 2.

4 Simulation Results

To investigate the effectiveness and robustness of the proposed schemes, numerical simulations are carried out for four different cases in Matlab R2016b under Windows 10 on a computer with 3.60 GHz CPU /12.0 GB RAM. Monte

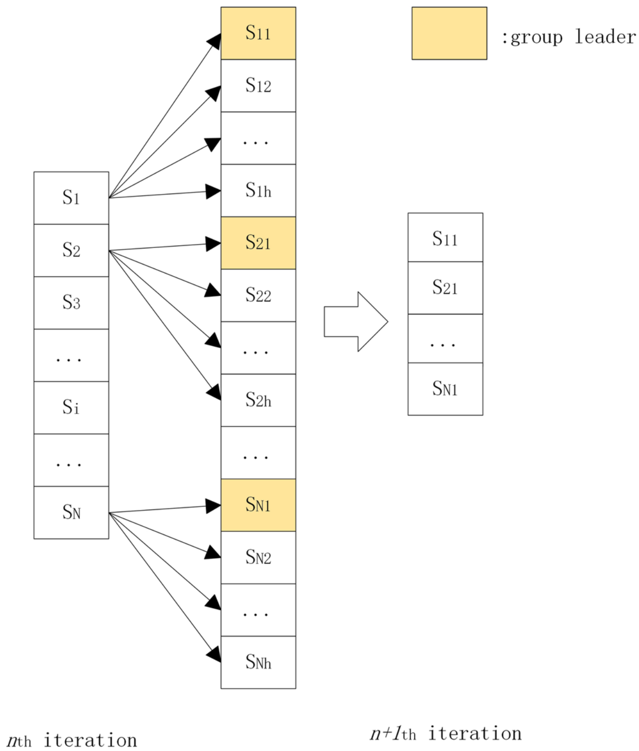

Fig. 1 Block diagram of IEGEA

Carlo simulations with random feasible initial values are carried out to demonstrate the robustness of the proposed evolutionary algorithms (SA, PSO, WEGSA, WEGPSO, IEGSA and IEGPSO). The simulations are performed on a 50-runs basis for each of the four cases and for each of the six algorithms. The performance of the six algorithms together with MILP can be compared from different standpoints, such as maximum sampling value (Max SV), mean sampling value (Mean SV), standard deviation of sampling value (Std SV), travel distance (TD), sampling value collected per kilometer (SV/km) and mean execution time (MET).

As mentioned in the section ”Problem Formulation”, the ocean sampling field for different case studies is a 2D discrete temperature nowcast map represented by a grid map of 80×60 grids.

The parameter setting is given in Table 1. Parameter setting in evolutionary algorithms is a crucial task and have been extensively studied in many literatures [22, 37–40]. Based on these researches, larger values of c_1 and c_2 in PSO or smaller values of T_0 and α in SA would push the path planners to converge faster but also would result in converging to local optimal solutions; on the contrary, it would take a large amount of computation time in finding global optimal solutions for path planners with smaller values of c_1 and c_2 in PSO or larger values of T_0 and α in SA. Since each algorithm has its own particular parameters, the parameter values in SA and PSO are selected based on the suggestions in literatures [22, 38], where these parameter values have been proven to provide good performance.

Fig. 2 Block diagram of WEGEA

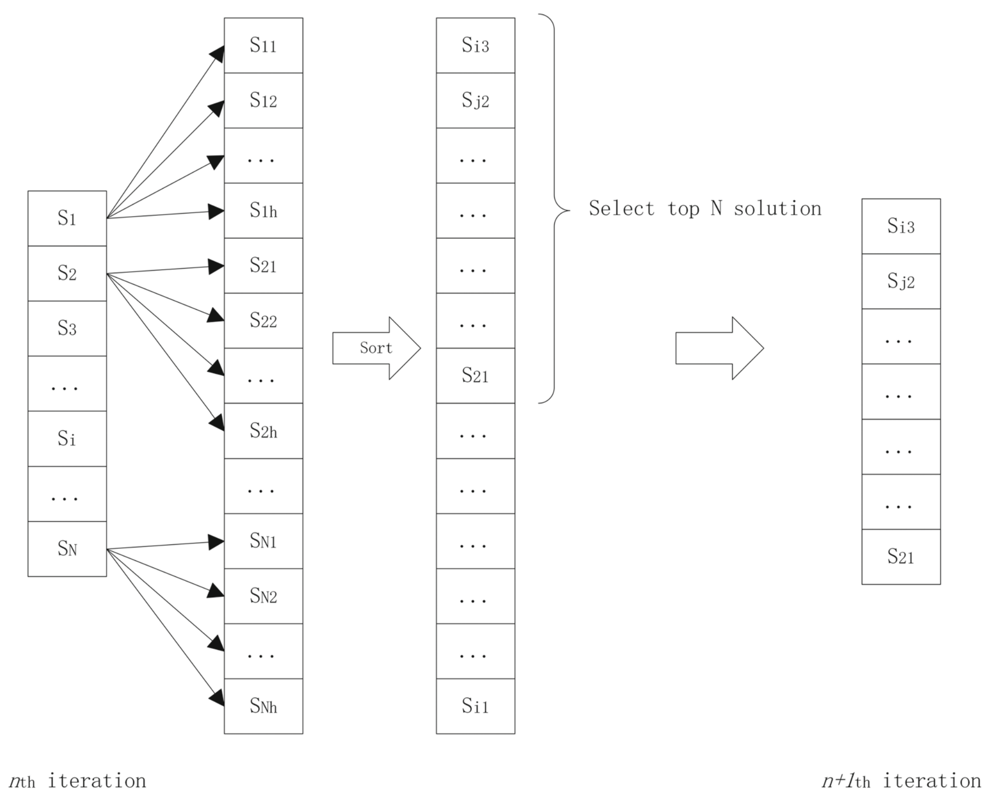

Table 1 Parameter value

Parameters		Value
Water-referenced speed of UMV		2m/s
Start point		(40,45)
Final point		(40,15)
Iterations		300
Population size	Conventional evolutionary algorithms	2500
	EGEA	500
SA	Initial temperature T_0	10
	Temperature reduction rate α	0.96
	Initial movement range η	15
	Damping ratio η_{damp}	0.97
PSO	Constant coefficient c_1 and c_2	2
	Initial weight factor w	1
	Damping ratio w_{damp}	0.99

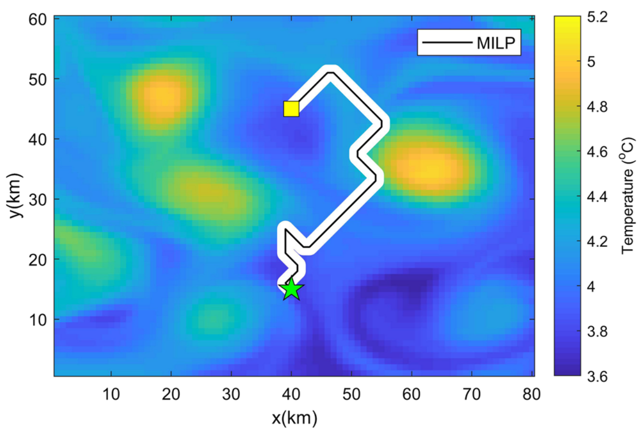

Fig. 3 Globally planned trajectory generated by MILP of case 1. The color map corresponds to ocean temperature magnitude. The temperature rises as the color turns from blue to yellow. The start and final points are represented in yellow square and green pentagram. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

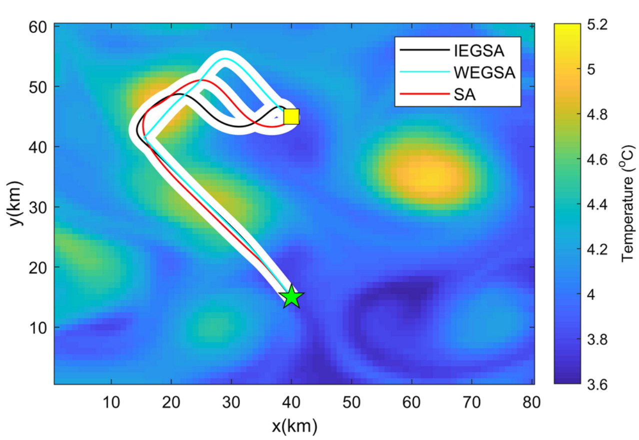

Fig. 4 Globally planned trajectories generated by IEGSA, WEGSA and SA of case 1

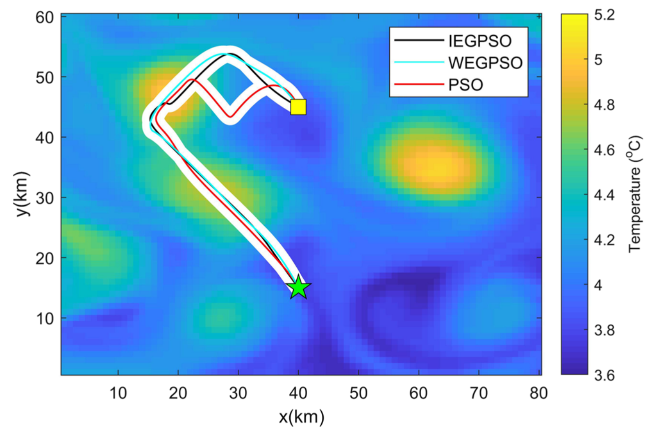

Fig. 5 Globally planned trajectories generated by IEGPSO, WEGPSO and PSO of case 1

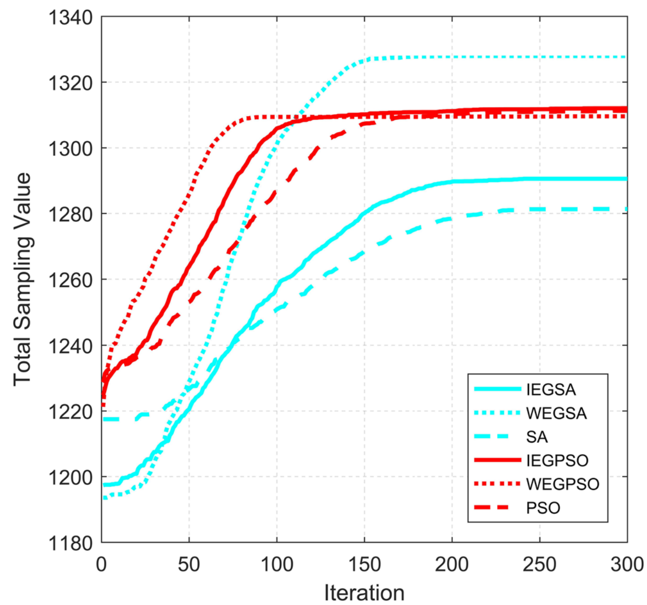

Fig. 6 Convergence curve of IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based on mean total sampling value of case 1

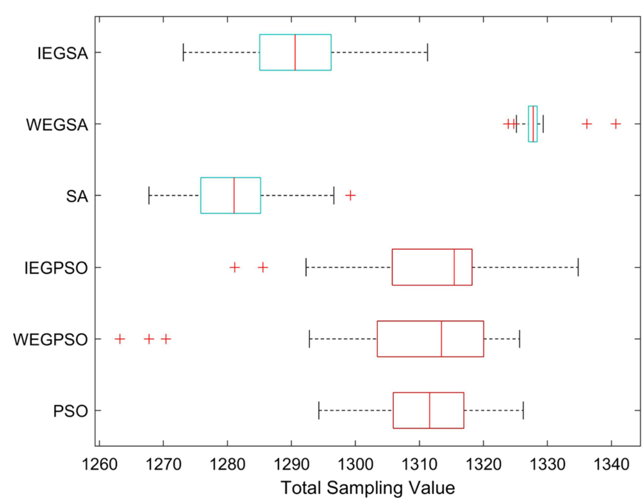

Fig. 7 Comparison of path planners based on case 1 in 50-runs Monte Carlo simulations

Table 2 Performance comparison of MILP, IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based path planners of CASE 1

Algorithms	Max SV	Mean SV	Std SV	TD (km)	SV/km	MET(s)
MILP	959	/	/	66.57	14.41	8.35
IEGSA	1311(**36.7%**)	1291(**34.6%**)	8.97	69.90	18.76(**30.2%**)	617
WEGSA	1341(**39.8%**)	1328(**38.5%**)	2.53	69.99	19.16(**33.0%**)	682
SA	1299(**35.5%**)	1281(**33.6%**)	6.97	69.77	18.62(**29.2%**)	626
IEGPSO	1335(**39.2%**)	1312(**36.8%**)	10.95	69.92	19.09(**32.5%**)	602
WEGPSO	1326(**38.3%**)	1310(**36.6%**)	14.13	70.00	18.94(**31.4%**)	774
PSO	1326(**38.3%**)	1311(**36.7%**)	7.79	69.96	18.95(**31.5%**)	551

(The percentage value in bold font indicate the percentage of improvement of the proposed EGEA path planners compared to MILP)

4.1 CASE 1: Path Planning for Single UMV with Fixed Start Point and Final Point

In case 1, an UMV, whose maximum range is only 70km, is set to start from a given position to collect as much information as possible before arriving the destination. Global off-line paths computed by MILP and three versions of SA and PSO are illustrated in Figs. 3, 4 and 5, respectively. As can be seen on Fig. 6, PSO converges faster than SA in each version. As for different selection methods, WPES is the first to converge, while conventional method is the last. The reason is that the population of conventional method is five times that of WPES, which increase the diversity of results but slow down the convergence speed. As can be seen on Fig. 7, as for mean sampling value, the difference between three versions of SA is larger than that of PSO, which demonstrates that the proposed schemes provide more positive effect for SA than PSO.

Statistic results are recorded in Table 2, where the percentage of improvement of each EGEA over MILP is presented in brackets. Travel distance of the UMV in each algorithm is within the maximum range of the UMV, which indicates that each algorithm can generate trajectory that guarantees the UMV to reach its destination before it runs out of energy. It can be observed from the Table 2 that WEGSA generates trajectory with the most sampling value (39.8% more than that of MILP), the most sampling value collected per kilometer (33.0% more than that of MILP) and the smallest standard deviation, while conventional SA and IEGSA perform poorly in finding high ocean temperature zones, as the mean sampling value of both are relatively low. On the other hand, each version of PSO gains similar mean sampling value, and conventional PSO performs better than the other two versions with regard to standard deviation and execution time. In addition, mean execution time for MILP method is much less than the proposed EGEA planner, due to the characteristics of MILP that searches the trajectory greedily without iteration. Undoubtedly, this leads to much less sampling value collected in the planned trajectory of MILP than the planned trajectory of EGEA. This research focuses on developing an effective global offline path

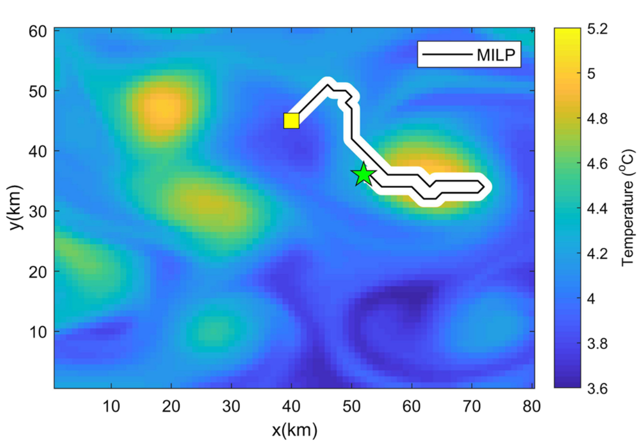

Fig. 8 Globally planned trajectory generated by MILP of case 2.

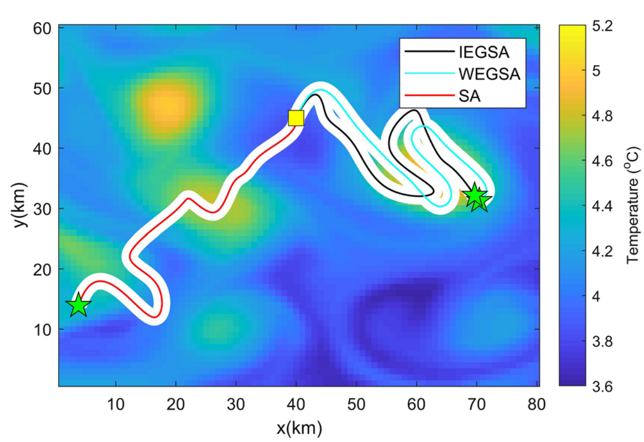

Fig. 9 Globally planned trajectories generated by IEGSA, WEGSA and SA of case 2

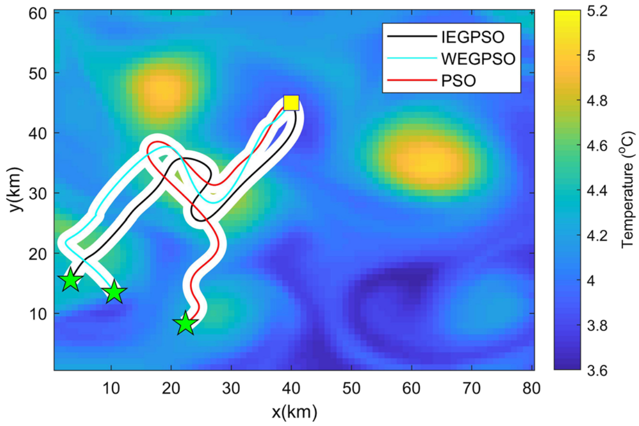

Fig. 10 Globally planned trajectories generated by IEGPSO, WEGPSO and PSO of case 2

planner for ocean sampling and execution time is one of the index. Since the mean sampling value, the sampling value collected per kilometer and the standard deviation reflect the searching ability and stability, it can be concluded that the WEGSA achieves better searching ability and stability than other algorithms in spite of longer execution time compared to other algorithms.

4.2 CASE 2: Path Planning for Single UMV with Fixed Start Point and Free Final Point

In case 2, an UMV, whose maximum range is only 70km, is set to start from a given position to collect as much information as possible before fuel is depleted. Global off-line paths computed by MILP and three versions of SA and PSO are illustrated in Figs. 8, 9 and 10, respectively. As can be seen on Figs. 11 and 12, similar to the fixed final point case, PSO converges faster than SA in each version; WPES is always the first to converge, while conventional method is the last; the difference between three versions of SA is larger than that of PSO in terms of mean sampling value.

Comparisons between the resulted trajectories and their qualities are shown in Table 3. It can be observed that the performance of MILP is poorer than other techniques. The reason is that MILP plans the trajectory without looking forward, hence, prone to fall into local optimum. It can be noted that the stability of PSO is poorer than SA for free final point case. Meanwhile, searching ability of WEGSA outperforms other algorithms, but stability and execution time of WEGSA are not as good as the other two versions of SA. Since the purpose of this research is to collect as much sampling information as possible in the region of high ocean temperature, the first priority is to select the algorithm with most sampling value and that refers to WEGSA.

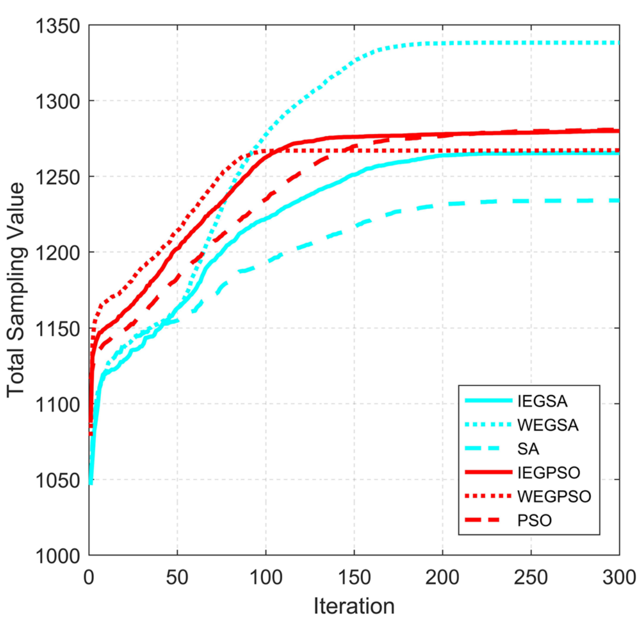

Fig. 11 Convergence curve of IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based on mean total sampling value of case 2

4.3 CASE 3: Path Planning for Multi-UMVs with Fixed Start Point and Final Point

In case 3, two vehicles are deployed to take measurements in the given research region with fixed start point and final point, assuming that the maximum range of one UMV is 50km while the other is 60km. Global off-line paths computed by MILP and three versions of SA and PSO are illustrated in Figs. 13, 14 and 15, respectively. As can be seen on Fig. 16, the curve tendency is similar to the single UMV case. In Fig. 17, it should be noted that the distribution of the results of sampling value of WEGSA is very tight, while that of WEGPSO is the most spread out.

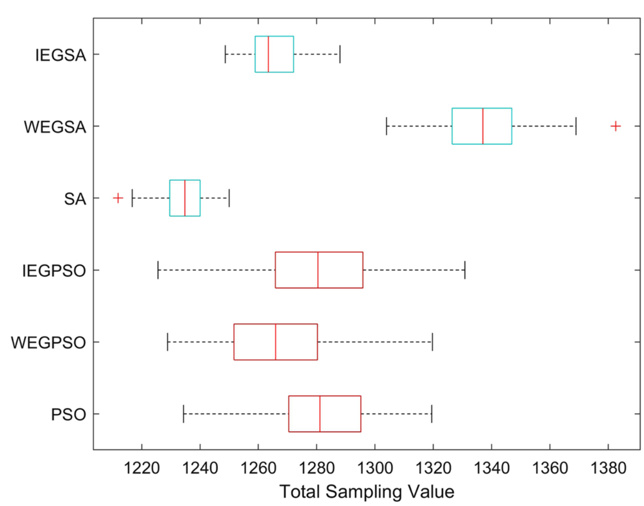

Fig. 12 Comparison of path planners based on case 2 in 50-runs Monte Carlo simulations

Table 3 Performance comparison of MILP, IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based path planners of CASE 2

Algorithms	Max SV	Mean SV	Std SV	TD (km)	SV/km	MET(s)
MILP	952	/	/	69.77	13.64	7.46
IEGSA	1288(**35.3%**)	1265(**32.9%**)	9.15	69.82	18.45(**35.3%**)	658
WEGSA	1383(**45.3%**)	1338(**40.6%**)	16.03	69.95	19.77(**44.9%**)	705
SA	1250(**31.3%**)	1234(**29.6%**)	9.18	69.90	17.88(**31.1%**)	670
IEGPSO	1331(**39.8%**)	1280(**34.5%**)	22.90	69.98	19.02(**39.4%**)	595
WEGPSO	1320(**38.7%**)	1267(**33.1%**)	20.78	69.98	18.86(**38.3%**)	759
PSO	1319(**38.6%**)	1281(**34.6%**)	19.48	70.00	18.84(**38.1%**)	567

(The percentage value in bold font indicate the percentage of improvement of the proposed EGEA path planners compared to MILP)

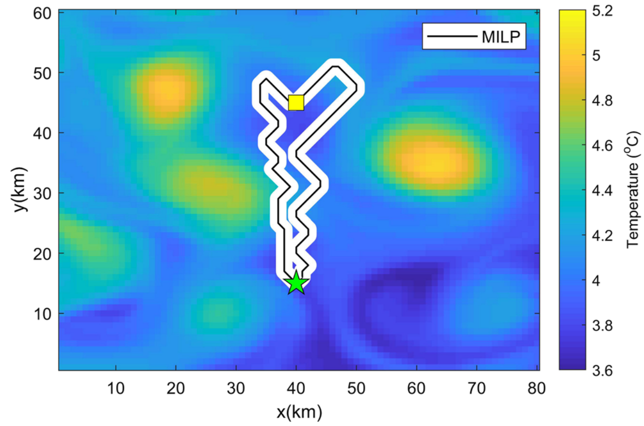

Fig. 13 Globally planned trajectories generated by MILP of case 3

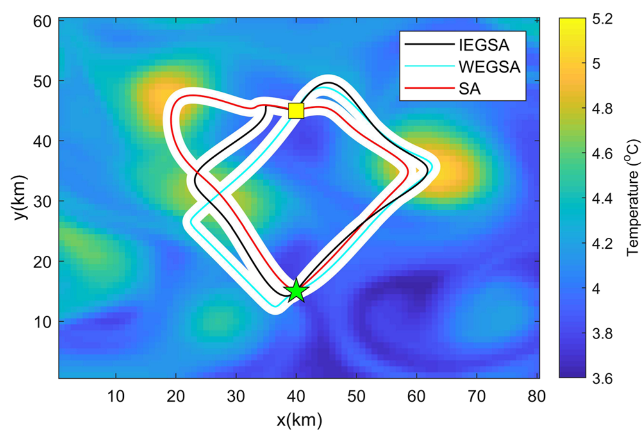

Fig. 14 Globally planned trajectories generated by IEGSA, WEGSA and SA of case 3

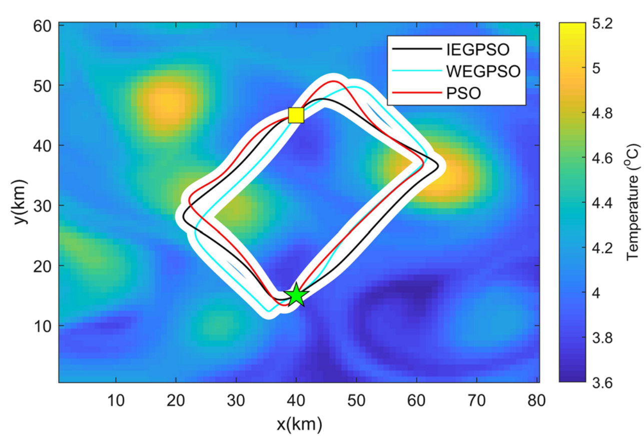

Fig. 15 Globally planned trajectories generated by IEGPSO, WEG-PSO and PSO of case 3

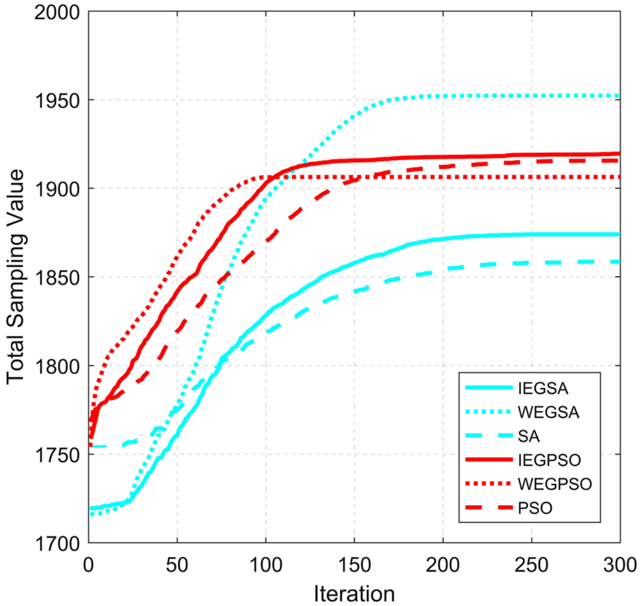

Fig. 16 Convergence curve of IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based on mean total sampling value of case 3

From the statistic results shown in Table 4, the maximum sampling value of WEGSA is the most among all other EGEA from 50-runs Monte Carlo simulation and dramatically 48.0% more than that of MILP. In addition, the sampling value collected per kilometer of WEGSA is 41.6% more than that of MILP, which shows the efficiency of the proposed EGEA path planners. It is obvious that WEGSA plans the paths with the most sampling value, the lowest standard deviation and the least execution time compared with those of other evolutionary methods, which further demonstrates the high performance and robustness of WEGSA.

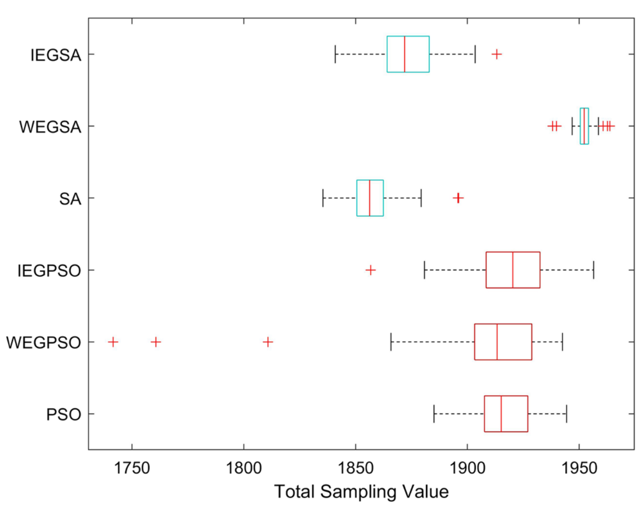

Fig. 17 Comparison of path planners based on case 3 in 50-runs Monte Carlo simulations

Table 4 Performance comparison of MILP, IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based path planners of CASE 3

Algorithms	Max SV	Mean SV	Std SV	TD (km)	SV/km	MET(s)
MILP	518+809= 1327	/	/	47.70+57.50= 105.20	12.61	12.89
IEGSA	887+1026= 1913(**44.2%**)	1874(**41.2%**)	15.02	49.77+59.80=109.57	17.46(**38.5%**)	1272
WEGSA	931+1033= 1964(**48.0%**)	1952(**47.1%**)	4.33	50.00+59.95=109.95	17.86(**41.6%**)	1247
SA	894+1002= 1896(**42.9%**)	1858(**40.0%**)	12.43	49.89+59.99=109.88	17.26(**36.9%**)	1274
IEGPSO	921+1035= 1956(**47.4%**)	1920(**44.7%**)	19.73	49.99+59.92=109.91	17.80(**41.2%**)	1260
WEGPSO	913+1030= 1943(**46.4%**)	1906(**43.6%**)	39.66	49.43+59.90=109.33	17.77(**40.9%**)	1257
PSO	918+1026= 1944(**46.5%**)	1916(**44.4%**)	14.62	49.93+59.94= 109.87	17.69(**40.3%**)	1264

(The percentage value in bold font indicate the percentage of improvement of the proposed EGEA path planners compared to MILP)

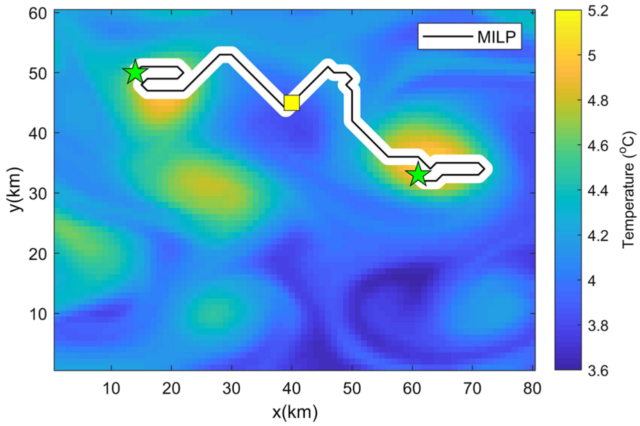

Fig. 18 Globally planned trajectories generated by MILP of case 4

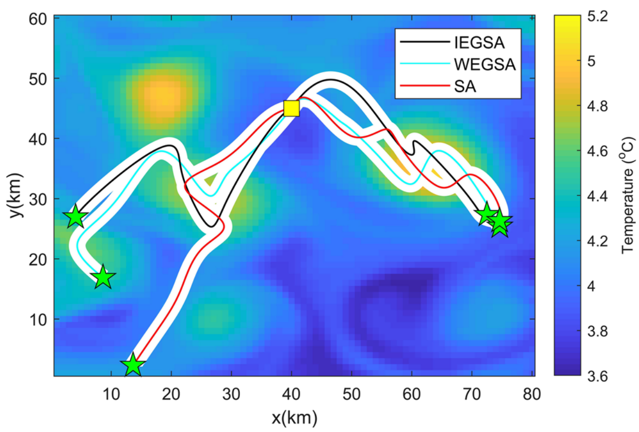

Fig. 19 Globally planned trajectories generated by IEGSA, WEGSA and SA of case 4

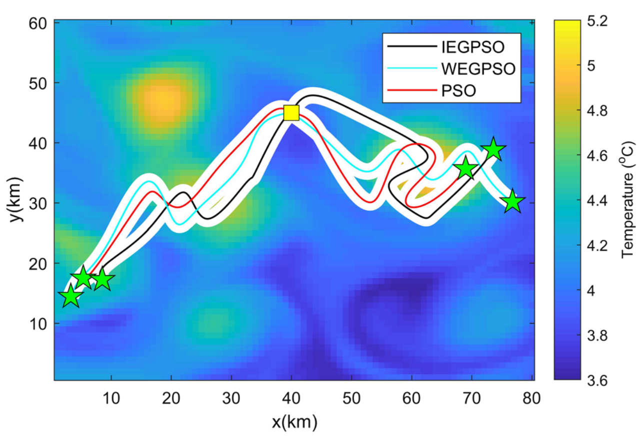

Fig. 20 Globally planned trajectories generated by IEGPSO, WEGPSO and PSO of case 4

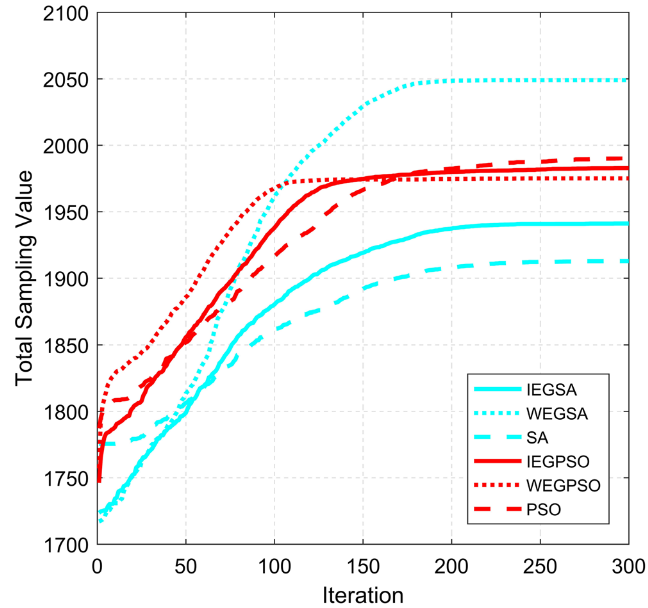

Fig. 21 Convergence curve of IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based on mean total sampling value of case 4.

4.4 CASE 4: Path Planning for Multi-UMVs with Fixed Start Point and Free Final Point

In case 4, two vehicles are deployed to take measurements in the given research region with fixed start point and free final point, assuming that the maximum range of one UMV is 50km while the other is 60km. Global off-line paths computed by MILP and three versions of SA and PSO are illustrated in Figs. 18, 19 and 20, respectively. Figures 21 and 22 shows simulation results of case 4, which demonstrate that the searching ability of WEGSA outperforms other methods.

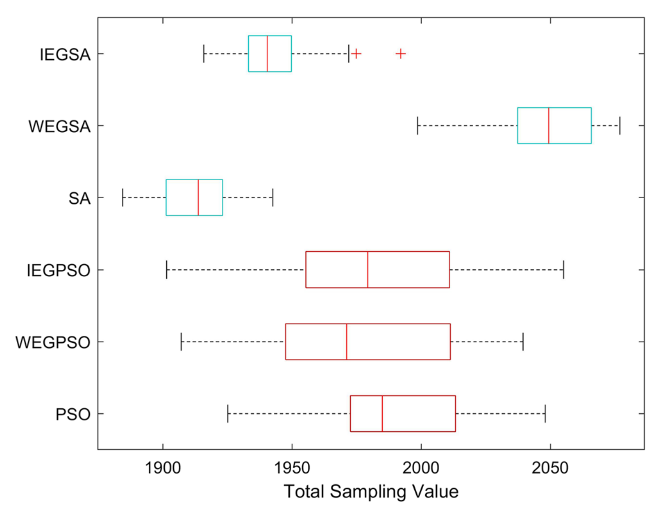

Fig. 22 Comparison of path planners based on case 4 in 50-runs Monte Carlo simulations

Table 5 Performance comparison of MILP, IEGSA, WEGSA, SA, IEGPSO, WEGPSO and PSO based path planners of CASE 4

Algorithms	Max SV	Mean SV	Std SV	TD (km)	SV/km	MET(s)
MILP	665+851=1516	/	/	48.70+59.53=108.23	14.01	11.76
IEGSA	934+1058=1992(**31.4%**)	1941(**28.0%**)	15.11	49.80+59.84=109.64	18.17(**29.7%**)	1251
WEGSA	973+1104=2077(**37.0%**)	2049(**35.2%**)	20.06	49.94+59.88=109.82	18.91(**35.0%**)	1250
SA	911+1032=1943(**28.2%**)	1913(**26.2%**)	13.71	49.84+59.91=109.75	17.70(**26.3%**)	1263
IEGPSO	954+1101=2055(**35.6%**)	1983(**30.8%**)	34.69	50.00+59.96=109.96	18.69(**33.4%**)	1266
WEGPSO	957+1082=2039(**34.5%**)	1975(**30.3%**)	36.00	49.68+59.97=109.65	18.60(**32.8%**)	1266
PSO	950+1098=2048(**35.1%**)	1990(**31.3%**)	28.30	49.98+59.94=109.92	18.63(**33.0%**)	1259

(The percentage value in bold font indicate the percentage of improvement of the proposed EGEA path planners compared to MILP)

Detailed simulation results are listed in Table 5. Although standard deviation of WEGSA is a little larger than the other two versions of SA, WEGSA finds the optimized paths quickly and returns the most sampling value. In addition, the standard deviation of PSO for each version is too large to be used to solve this problem. Therefore, WEGSA is superior to all other algorithms in this case study.

4.5 Discussions

Based on the results of the above four case studies, two issues need to be discussed here. Firstly, it can be observed that MILP performs worst when compare to the proposed six EGEA. The reason is that MILP without heuristic information cannot search the workspace in an effective manner, consequentially, it returns sub-optimal solutions. Secondly, the GIES method gives the best results for the PSO algorithm, while the WPES method for the SA algorithm. This is due to the difference between the principle of SA and PSO. Each particle in PSO is manipulated to keep track of its own best position, which refers to p_{best} in Eq. 9. However, the proposed WPES method intends to select and keep particles with good solutions and abandon particles with poor solutions, which causes constantly huge changes in the best position of each particle and results in disturbing the inheritance of particle itself. On the other hand, GIES method can help each particle to select its best child and keep track of its own best position in iterations. Hence, PSO integrated with GIES method can produce better solutions than PSO integrated with WPES method. When it comes to SA, the principle of SA is always to keep child individuals of the next generation with better solutions and to accept child individuals with worse solutions in a certain probability. Both GIES and WPES methods have positive effects on searching global optimized solutions for SA. Since WPES method focuses on selecting the whole population elitists, WPES method is preferable to SA.

5 Conclusion

This paper presents a novel elite group-based evolutionary algorithm for maximum ocean sampling of multi-UMVs. Simulated annealing and particle swarm optimization are introduced in this research to solve the adaptive ocean sampling problem. Simulations have been conducted to find offline optimized trajectories with maximum sampling value in the regions of high scientific interest with constrained energy of UMVs in an available cost map. Based on the results of four case studies, the WEGSA shows its potential of generating optimized trajectories with more sampling value, lower standard deviation and less execution time than those of other techniques. More specifically, WEGSA shows higher searching accuracy, stronger robustness and faster convergence when solving the path planning problem associating with adaptive ocean sampling.

Future work involves to apply realistic ocean currents information into the proposed scheme and take collision avoidance into consideration. Another extension of this work is to develop on-line path re-planning strategy for adaptive ocean sampling of UMVs and to extend the proposed scheme to 3D workspace. Furthermore, a robust and intelligent navigation, guidance and control (NGC) system is vital for UMV. The integration of the path planning module with control module is a another potential work in the future.

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